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Investigating the spatial variability of some important groundwater quality factors based on the geostatistical simulation (case study: Shiraz plain)

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A B S T R A C T

The management of groundwater plays a vital role in arid and semiarid regions. An assessment of groundwater suitability for irrigation is essential for a sustainable food production. In this study, efficiencies of three interpolation techniques such as inverse distance weighting, kriging and cokriging for simulation of groundwater quality indices for irrigation such as: pH, Mg^{2+}, Ca^{2+}, Na^{+}, TH, electrical conductivity (EC), sodium absorption ratio (SAR), Cl^{-} and SO_4^{2-} were compared. The spatial structure results show that the variograms and cross-validation of the nine variables can be modeled with three methods, namely the inverse distance weighting, kriging and cokriging. The relevant data from 56 wells (with the depth between 30 and 60 m and diameter usually between 10 and 20 cm) in suburb of Shiraz were collected. After normalization of data, variograms were computed. Optimum variogram was selected based on least square value analysis. Then, by using cross-validation, mean error and root mean square error analysis, the interpolation model was selected. Results showed that for Mg^{2+}, Ca^{2+}, TH, EC, Cl^{-} and SO_4^{2-} cokriging had the lowest root mean square error, and for SAR and Na+ inverse distance weighting technique and for pH, kriging had better results comparing geostatistical method to simulate groundwater quality indices. For pH, TH, EC, and Mg^{2+} data; for SAR, Ca^{2+}, Na^{+}, and Cl^{-} data; and for SO_4^{2-} data, spherical, Gaussian model, and exponential were proved to be the best semivariogram models, respectively. Moreover, the results illustrated that cokriging method was the best due to its highest precision and lowest error. Finally, the geographic information system can fully display spatial patterns of quality factors in groundwater resources of the study area.

Keywords: Groundwater quality; Interpolation; Geostatistics; GIS; Shiraz city

1. Introduction

Groundwater is one of the most significant natural resources [1,2]. Its quality is influenced by the geological formation and anthropogenic activities, e.g., changes in land use, urbanization, intensive irrigated agriculture, mining activities, disposal of untreated sewage in river, lack of rational management, etc. [3]. The groundwater contamination may cause various diseases and other problems too [4–6]. In the process of mapping groundwater quality, two main stages can be distinguished: (1) the sampling stage and (2) the prediction stage, during which the observations are interpolated to a fine grid. The quality of the resulting map is determined by both stages. Geostatisticians have concentrated most on the second stage, by applying various types of interpolation methods [7,8]. Geostatistics is a spatial statistical procedure that can be used to assess and represent the distribution of concentration over space and time [9,10]. The method predicts the estimated values based on the relationship between the sample points and estimates the uncertainty of the results [11–13]. Geostatistical methods, which are considered as powerful tool for interpolation, have been applied

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in different branches of science, such as earth science, hydrogeology, soil science, mining and hydrometeorology [14–16]. Recently, geostatistical tools have also been applied in the modeling of the spatial distribution in many disciplines, and they are increasingly coupled with geographical information system (GIS) capabilities for applications that characterize the space structure (semivariogram analysis), spatially interpolating scattered measurements to create spatially exhaustive layers of measured parameters [17,18].

Commonly used methods applied in spatial statistics include: ordinary kriging, cokriging and inverse weighted distance (IWD). Kriging is regarded as the best linear unbiased estimation. Many studies have successfully used interpolation techniques with and without the use of the ArcGIS geostatistical tool [19–21]. Few researchers have applied the integration of geostatistical techniques and vulnerability assessment as a new approach for redesigning the groundwater monitoring networks [22]. The density of monitoring wells was considered together with vulnerability assessments by Dawoud [23]. Yeh et al. [24] applied a genetic algorithm and the factorial kriging method for nine variables: electrical conductivity (EC), total dissolved solids (TDS), Cl^-, Na^+, Ca^{2+}, Mg^{2+}, SO_4^{2-}, Mn and Fe^- for optimal selection of monitoring wells in Pingtung plain, Taiwan. Nazari-zade et al. [25] used geostatistics method to study spatial variability of groundwater quality in Balarood plain. Their results showed that spherical model is the best model for fitting on experimental variogram of EC, Cl^- and SO_4^{2-} variables. Ahmed [26] applied kriging to assess the spatial dependencies of the water quality variables such as TDS and concluded that kriging has high capability of application. Barca and Passarella [27] used disjunctive kriging and simulation methods to make nitrate risk map in 10 and 50 mg/L thresholds, in Modena plain of Italy.

The vulnerability of groundwater is characterized by the hydrogeological and geological attributes of the aquifer to specific areas that are more vulnerable to contamination [28]. The DRASTIC model is the most commonly applied vulnerability model based on the physical environmental aquifer parameters to assess groundwater vulnerability [29–31]. Delgado et al. [32] used kriging to map groundwater quality parameters in Yucatan, Mexico. Based on the generated maps, they classified the study area into different zones in terms of water quality for agricultural uses. Adhikary et al. [33] analyzed spatial variability of groundwater quality in India. They produced probability maps of groundwater contaminants using indicator such as kriging. Houshmand et al. [34] used cokriging and kriging methods for spatial estimation of sodium absorption ratio (SAR) and chloride (Cl) concentration in groundwater [34]. For SAR and Cl data, Gaussian model was proved to be the best semivariogram model. Kriging methods were also used by Rawat et al. [35] to predict spatial distribution of groundwater quality parameters. Because of various results reported by abovementioned researchers, it is obvious that suitable method of interpolation to estimate one variable depends on variable type and regional factors; thus, any selected method for specific region cannot be a generalized scheme.

Geostatistical analysis provides a series of statistical models and tools for spatial data exploration and surface generation of groundwater quality [4,36]. The present study investigated the spatial distribution of the water quality parameters of Shiraz plain (Fars province, Iran). Geostatistical methods were applied in order to determine the most suitable method that can be used to develop spatial variability maps and study the variability of the groundwater quality parameters. First, the hydrogeological setting of the study area was investigated using drilling, pumping tests and geophysical data. Secondly, the general characteristics of groundwater quality data and the accuracy of different interpolation methods (ordinary kriging, cokriging and IWD) were examined.

2. Materials and methods

Shiraz plain, covering an area of roughly 300 km^2 with local coordinates of 52°32′ E longitude and 29°36′ N latitude and having an average altitude of 1,500 m, is located in Fars province, in the south of Iran, in a climatologically arid and semiarid region. Shiraz plain is stretched from north to Babakoohi and Kaftarak mountains, from northwest to Derak mountain, from south to Sabzpooshan and Soltanabad mountains, and from west and southwest to Polfasa mountain and Maharloo lake. Studies have shown that the Shiraz alluvial plain is layered and clay layers are located between the aquifers. The alluvial sedimentation does not have a uniform thickness, and sandy layers are located between silt and clay layers. Also, geophysical explorations indicate that Shiraz plain aquifer goes down as far as 150 m deep, and at depth below that if there is an aquifer layer at all, it does not have a good quality [37,38]. Furthermore, the alluvium structure in the west plain is mainly coarse grain, and it turns to fine grain near Maharloo lake. One of the largest wheat-producing regions in Iran is located in the Shiraz plain, Fars province [39]. The geochemical characteristics of groundwater within the study area was carried out based on chemical analyses of water samples collected in January 2012 at 40 sampling locations. The location of groundwater study area and distribution of wells is shown in Fig. 1. The sampling sites are distributed in a systematic manner in the region.

2.1. Methodology

The objective of this study is to evaluate the accuracy of various interpolation methods such as kriging, cokriging

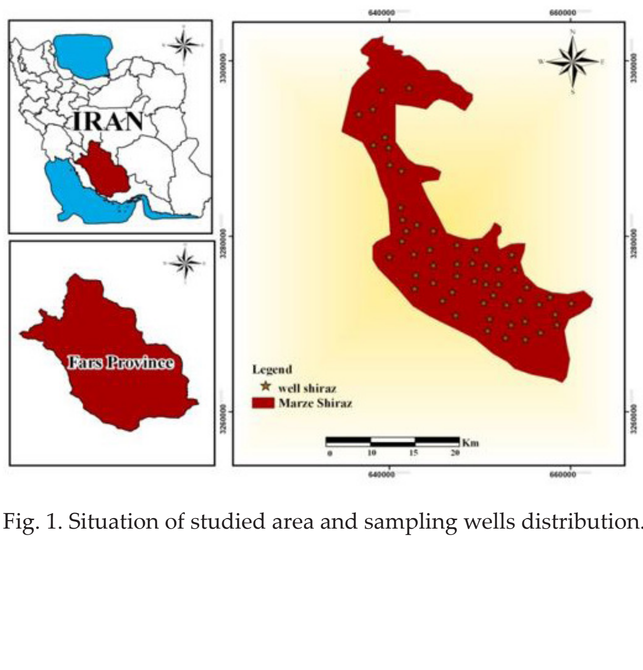


Fig. 1. Situation of studied area and sampling wells distribution.

and inverse distance weight (IDW), for prediction of groundwater assessment parameters in Shiraz region. In this study which is for spatial prediction of groundwater quality of the Shiraz plain, 56 sets of data from Shiraz regional water district (SRWD) were used [37]. After normalization of data, kriging, cokriging and IDW methods were used for interpolating groundwater quality parameters. Finally, with the use of cross-validation, the optimum method of interpolation was selected. Then, we proceeded to prepare the map of groundwater quality parameters based on the interpolation techniques in GIS environment. The variograms are prepared by GS+ software. Fig. 2 shows the flow diagram of this study.

2.2. Spatial prediction methods

2.2.1. Kriging

The presence of a spatial structure where observations are close to each other and also they are more alike than those that are far apart (spatial autocorrelation) is a prerequisite to the application of geostatistics [40]. For the purpose of evaluating spatial distribution in groundwater parameters from each other, the variable mode was used. In general, the purpose of calculating the variable mode is to estimate changes in variables with respect to temporal and spatial variations. To calculate the variability, the total squared difference between pairs as a distance h from each other is determined and plotted against h, in a semivariogram, as given in Eq. (1) [41]:

$$\gamma(h) = 1/2Var[Z(x) - Z(X+h)] \quad (1)$$

where Var is the variance; $Z(x)$ is the observed value of one parameter at point x_i; and $Z(x + h)$ is the value of parameter at point $x_i + h$.

The variogram is some quantitative descriptive statistics that can be graphically represented in a manner that characterizes the spatial continuity (i.e., roughness) of a data set. In order to interpolate with different methods, a theoretical model must be fitted to the experimental data of the semivariogram. By correlating a theoretical model to the value of the empirical model and by applying linear and nonlinear models, unknown variables can be estimated [42]. This technique was developed to create mathematical models for a spatial correlation structure with a variogram that quantifies the spatial variability of random variables between two points [43]. In this study, three types of models (spherical, exponential and linear) were used to determine the optimum variable mode. Each hydrochemical parameter was analyzed under the aforementioned semivariogram models.

When you look at the model of a semivariogram, you will notice that at a certain distance the model levels out.

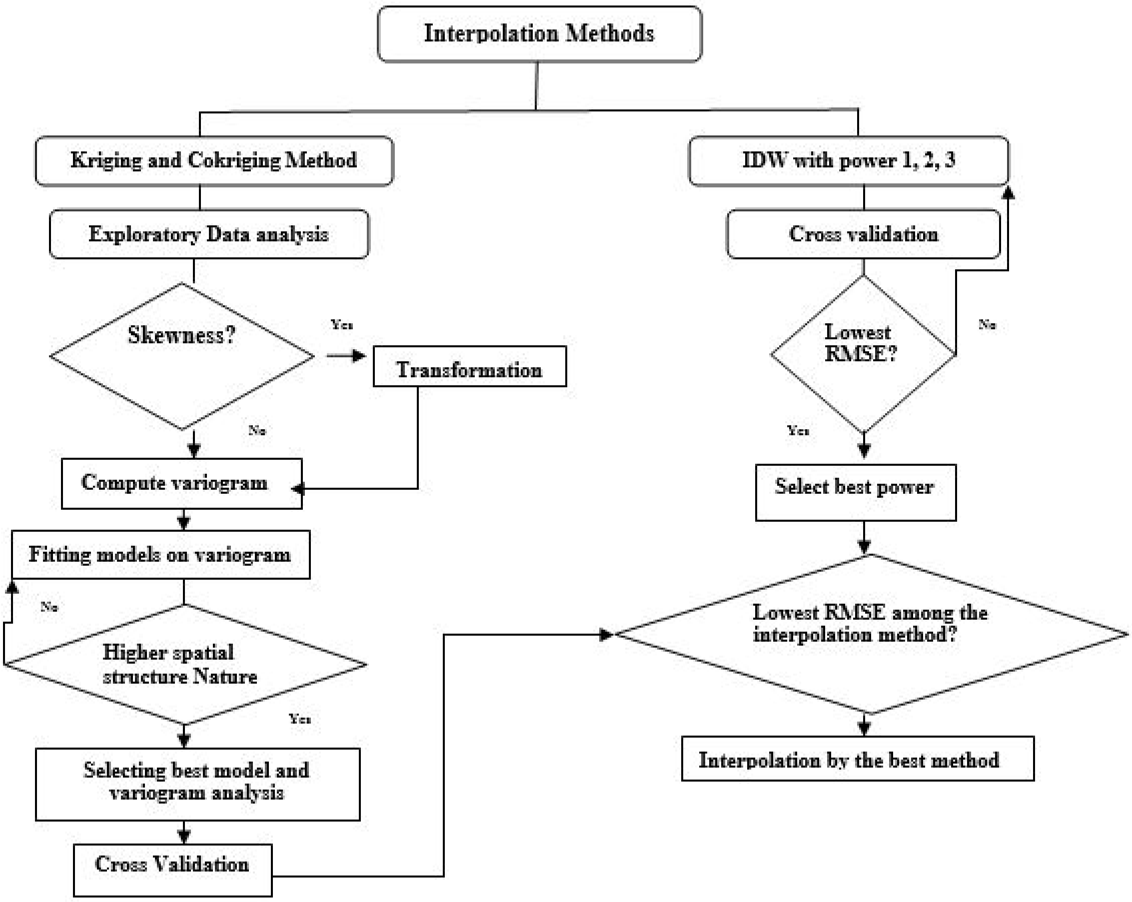


Fig. 2. Flow diagram of geostatistics study and selection of the best model for estimation of variable [7].

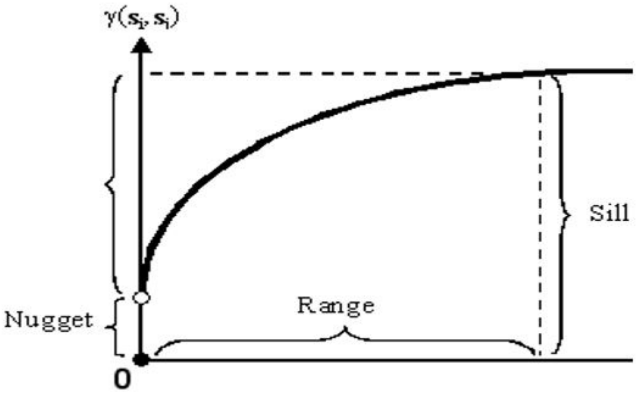


Fig. 3. The model of a semivariogram.

The distance where the model first flattens is known as the range. Sample locations separated by distances closer than the range are spatially autocorrelated, whereas locations farther apart than the range are not. The value at which the semivariogram model attains the range (the value on the y-axis) is called the sill. A partial sill is the sill minus the nugget. Theoretically, at zero separation distance (e.g., lag = 0), the semivariogram value is zero. However, at an infinitely small separation distance, the semivariogram often exhibits a nugget effect, which is a value greater than zero. If the semivariogram model intercepts the y-axis at 2, then the nugget is 2. The nugget effect can be attributed to measurement errors or spatial sources of variation at distances smaller than the sampling interval (or both). Measurement error occurs because of the error inherent in measuring devices. Natural phenomena can vary spatially over a range of scales. Variation at microscales smaller than the sampling distances will appear as part of the nugget effect. Before collecting data, it is important to gain an understanding of the scales of spatial variation in which you are interested [14]. Fig. 3 illustrates the model of semivariogram.

The ratio of nugget variance to sill expressed in percentages can be regarded as a criterion for classifying the spatial dependence of groundwater quality parameters. If this ratio is less than 25%, then the variable has strong spatial dependence; if the ratio is between 25% and 75%, the variable has moderate spatial dependence; and greater than 75%, the variable shows only weak spatial dependence [39].

2.2.2. Inverse weighted distance

In an interpolation technique such as IDW method, a weight is attributed to the point to be measured. The amount of this weight is depended to the distance of the point to another unknown point. These weights are controlled on the bases of power of ten. With increase of power of ten, the effect of the points that are farther diminishes. Lesser power distributes the weights more uniformly between neighboring points. We should keep in mind that in this method the distance between the points count, so the points of equal distance have equal weights. In this method the weight factor is calculated using the following formula:

$$\lambda_i = \frac{D_i^{-a}}{\sum_{i=1}^{n} D_1^{-a}} \tag{2}$$

where λ_i is the weight at point i; D_i is the distance of point i to an unknown point; and α is the power ten of the weighting [44].

2.2.3. Cokriging

The “Co-Regionalization“ (expressed as correlation) between two variables, i.e., the variable of interest, groundwater quality indices, and another easily obtained and inexpensive variable, can be extrapolated to the advantage of estimating purposes by the cokriging technique. In this sense, the advantages of cokriging are realized through reductions in costs or sampling effort. The cross-semivariogram is used to quantify cross-spatial autocovariance between the original variable and the covariate. The cross-semivariance is computed through the following equation:

$$\lambda\mu v = 1/2E[\{z\mu(x) - z\mu(x+h)\}\{z(v(x)) - zv(x+h)\}] \tag{3}$$

where $\lambda\mu\upsilon h$ is cross-semivariance between μ and υ variables; $z\mu(x)$ is as primary variable; and $z\upsilon(x)$ is the secondary variable [45].

2.3. Comparison between the different methods

In order to evaluate and select the best method of interpolation coefficient, the coefficient of determination of (R^2), root mean square error (RMSE) and mean absolute error (MAE) were used (Eqs. (4)–(6)).

$$R^2 = \frac{\sum_{i=1}^{n}\left[Xi(o) - X(mean)\right]2 - \sum_{i=1}^{n}\left[Xi(o) - X(p)\right]^2}{\sum_{i=1}^{n}\left[Xi(o) - X(mean)\right]^2} \tag{4}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[X_i(o) - X(p)\right]^2} \tag{5}$$

$$\text{MAE} = \frac{\sum_{i=1}^{n}\left|X_{i(o)-X_{i(p)}}\right|}{n} \tag{6}$$

In the above equations, n is the number of data; $X_i(o)$ is the measured value; X(mean) is the average of the measured values; and $X(p)$ is the estimated value [46,47].

Root sum squares (RSS) approach to tolerance analysis has a solid foundation in capturing the effects of variation. In the days of the golden abacus, there were no super-fast processors willing to calculate the multiple output possibilities in a matter of seconds (as can be done with Monte Carlo simulators on our laptops). It has its merits and faults but is generally a good approach to predict output variation when the responses are fairly linear and input variation approaches normality. That is the case for plenty of tolerance analysis dimensional responses so we will utilize this method on our nonlinear case of the one-way clutch [3].

3. Results

Many variables exhibit a nonnormal distribution of measured values and therefore do not initially satisfy the basic assumption of geostatistics of statistical normality. This restriction is eliminated, by applying a data transform to the sample values that make them more agreeable to analysis and estimation. The most useful data transform is the log-transform. Since natural log values can be back transformed to real values, we can use a semivariogram model derived from the transformed sample values to predict the spatial variation of logarithmic values of groundwater quality indices (GWQI). A statistical summary of the groundwater quality properties is presented in Table 1. As shown in Table 1, all parameters had high skewness; therefore, they were normalized using logarithmic method.

Our task now is to correlate models to the experimental or sample values choosing models and fitting them to data remaining, which is among the most controversial topics in geostatistics. There are still controversies who could fit models by eye and who defined their practice with vigor. They may justify their attitude on the grounds that when kriging is selected, the resulting estimates are much the same for all reasonable models of the variogram. We used a procedure that embodies both visual inspection and statistical fitting, as follows. First, experimental variogram is plotted. Then the models that hold one or more approximately the right shape and sufficient detail to achieve the principal trends in the experimental values are chosen. The best model for correlating on experimental variogram was selected based on least RSS values (Table 2).

Fig. 4 shows the variograms for groundwater parameters. Results showed that for TH and EC, spherical model was selected as the optimum model. In this model, it shows an almost linear increasing part, followed by a quite abrupt leveling of forward to sill. However, for other parameters such as SO_4^{2-}, the fitting model was exponential, and for SAR, Cl^- and Na^+, Gaussian model reaches the sill asymptotically, so no strict range was observed on the variables.

All parameters of groundwater quality have high spatial structure. Also, effective range of most parameters is close together with the range of 95–101 km. The effective distance demonstrates the distance that variogram has the highest value (Table 3).

First step for cokriging is computing of cross-variograms. The cross-variogram can be modeled in the same way as that of variograms, and the same restricted set of functions are available too. Having learned how to model the cross-variogram, we can use our knowledge of the spatial relations between two variables to predict their values by cokriging. Typically, the aim is to estimate just one variable, plus those of one or more other variable, which we

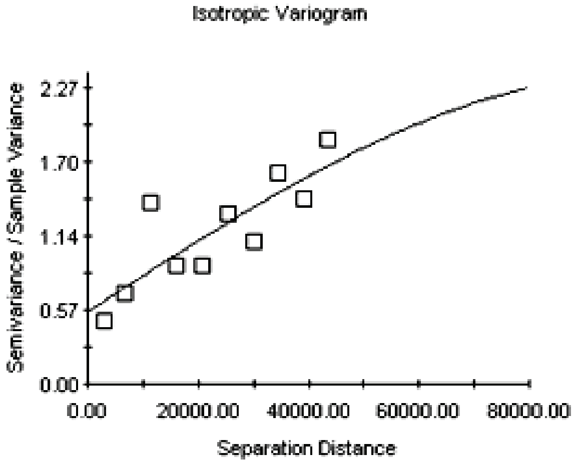
Table 2
Selection of the most suitable model for evaluation on experimental variogram according to RSS

Model			
GWQI	Gaussian	Exponential	Spherical
pH	0.055	0.059	0.042
TH	0.305	0.296	0.295
SAR	0.570	0.577	0.576
EC	0.546	0.526	0.514
SO_4^{2-}	0.649	0.631	0.648
Cl^-	0.644	0.676	0.672
Na^+	0.709	0.736	0.733
Ca^{2+}	0.110	0.12	0.117
Mg^{2+}	0.219	0.305	0.123

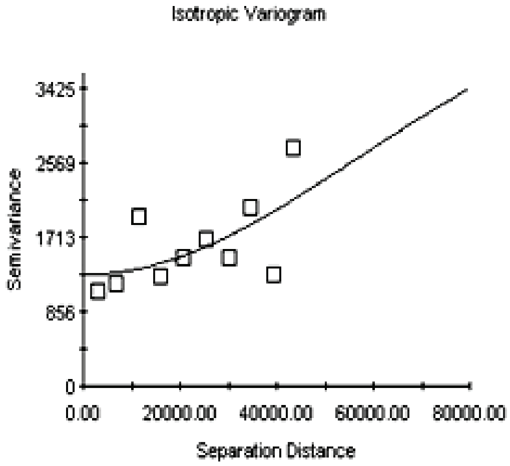
Table 1
Results of statistical analysis on groundwater quality

GWQI[a]	Min.	Max.	Mean	Standard deviation	Skewness	Kurtosis
pH	6.94	9.79	7.52	0.501	2.47	7.81
pH[b]	1.94	2.28	2.016	0.062	2.14	6.10
TH (meq/L)	140	5,000	1,141.7	1,126.4	2.148	6.984
TH[b] (meq/L)	4.94	8.51	6.69	0.818	0.262	2.87
SAR	0.013	26.693	2.044	4.302	4.823	25.924
SAR[b]	–4.34	3.28	–0.09	1.373	–0.983	5.681
EC (μS/cm)	522	19,073	2,696.8	3,160	3.253	15.162
EC[b] (μS/cm)	6.257	9.85	7.52	0.870	0.592	3.38
SO_4^{2-} (meq/L)	0.16	64.66	11.167	15.159	2.102	6.676
$SO_4^{2-,b}$ (meq/L)	–1.832	4.169	1.511	1.547	–0.462	2.604
Cl^- (meq/L)	0.45	237	13.538	36.918	5	28.33
$Cl^{-,b}$ (meq/L)	–0.798	5.468	1.585	1.232	0.520	4.625
Na^+ (mg/L)	0.02	174.02	9.240	27.726	5.09	28.25
$Na^{+,b}$ (mg/L)	–3.912	5.159	0.946	1.635	–0.730	5.260
Ca^{2+}	2	37.5	9.22	7.92	2.10	4.41
$Ca^{2+,b}$	0.69	3.62	1.94	0.727	0.36	–0.46
Mg^{2+}	0.5	67.5	11.42	15.350	2.84	7.48
$Mg^{2+,b}$	–0.69	4.21	1.901	1.021	0.17	0.4

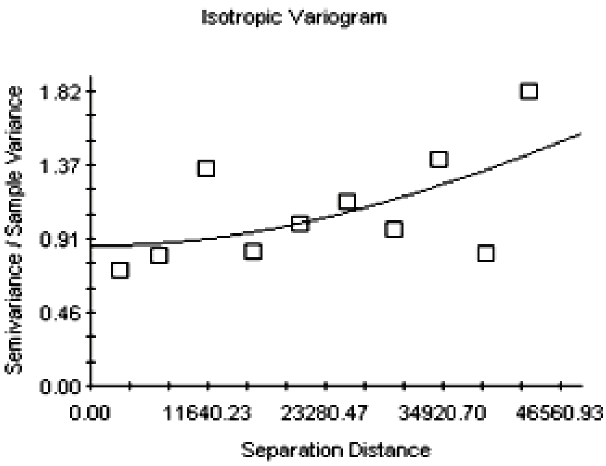
[a]GWQI: groundwater quality indices.
[b]Using logarithm to normalize data.



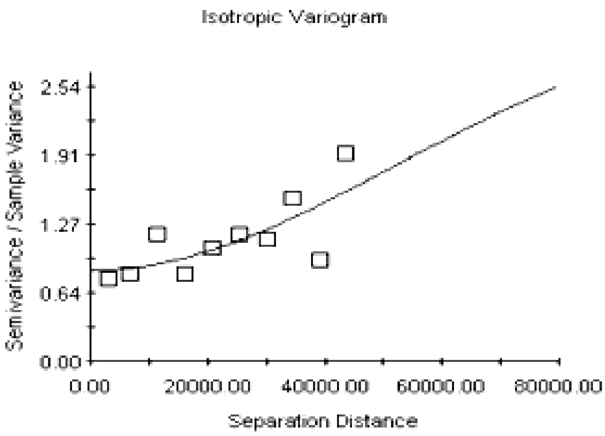
a) EC



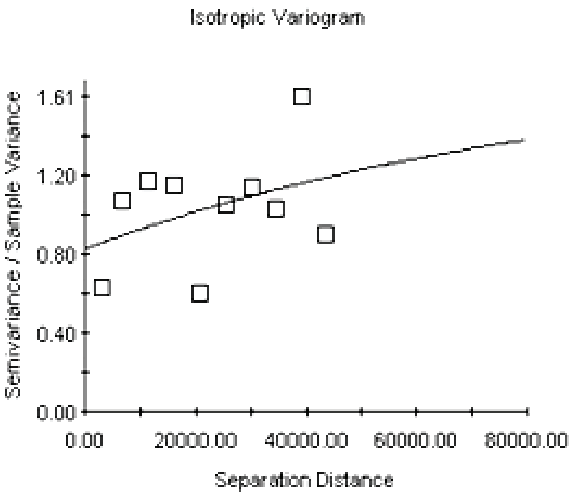
b) CL$^-$



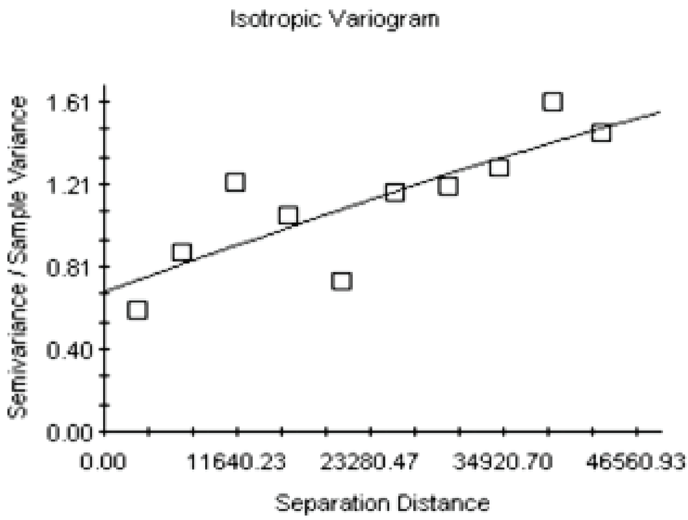
c) Na$^+$



d) SAR



e) So$_4^{2-}$



f) TH

Fig. 4. Variograms related to groundwater quality: (a) EC, (b) Cl$^-$, (c) Na$^+$, (d) SAR, (e) SO_4^{2-} and (f) TH.

Table 3
Best-fitted variogram models of groundwater quality and their parameters

GWQI	Model	Nugget %	Sill %	$\frac{C_{\circ}}{C_{\circ}+C}\%$	Å (km), range	R^2	RSS
pH	Spherical	0.086	0.235	0.634	7,010	0.086	0.042
TH (meq/L)	Spherical	0.628	1.94	0.64	95,660	0.66	0.295
SAR	Gaussian	0.839	3.26	0.74	101,100	0.500	0.570
EC (μS/cm)	Spherical	0.555	2.36	0.73	98,730	0.893	0.514
SO_4^{2-} (meq/L)	Exponential	0.828	1.756	0.52	87,500	0.146	0.631
Cl^- (meq/L)	Gaussian	0.864	3.15	0.72	79,930	0.386	0.644
Na^+ (mg/L)	Gaussian	0.865	3.94	0.72	96,290	0.341	0.709
Ca^{2+}	Gaussian	0.416	2.853	0.854	85,810	0.75	0.110
Mg^{2+}	Spherical	0.410	4.829	0.915	44,350	0.88	0.123

regard as auxiliary variable. To develop cross-variogram, a few samples are affiliated with the auxiliary samples, so cokriging should be reduced. Cross-variograms are presented in Fig. 5.

To determine the optimum method among kriging, cokriging and IDW, criterion of RMSE and MEA were used. Results showed that methods had cokriging more considerable accuracy than IDW method for parameters such as TH, EC, Cl^- and SO_4^{2-}. Otherwise, IDW showed higher accuracy comparing with geostatistical method for prediction of SAR and Na^+ parameters (Table 4). Finally, maps of groundwater quality for some parameters were prepared by cokriging and IDW, which were selected as optimum methods for interpolation in GIS software.

The analysis showed that to generate quantify data for groundwater quality index Mg^{2+}, Ca^{2+}, TH, EC, Cl^- and SO_4^{2-} cokriging would be performed better than kriging. And for characterizing the spatial variability IDW technique and for SAR cokriging had better result than other methods, which is in agreement with the work done by Ahmed [26], Nazari-zade et al. [25] and Rizzo and Mouser [40]. They also revealed that geostatistical methods could be the optimum model for groundwater data interpolation. This study shows the high capability of geostatistical tools for provision of maps of spatial structure of groundwater quality variables. Careful analysis of the measurement data using common sense can sometimes result in the same conclusions as those resulting from lengthy and computationally heavy calculations. For spacing beyond the range of spatial autocorrelation, kriging estimates reduce to the same results as for the classical random sampling. A geostatistical analysis is not only computationally intensive algorithms but also requires many samples to be taken and analyzed as acute as possible. As mentioned before, at least 30–50 pairs of observations are necessary to calculate one point of the experimental variogram. For the rest of groundwater quality indices such as Na^+ and SAR, IDW techniques have better result than geostatistical method to simulate groundwater quality indices (Figs. 6 and 7).

4. Discussion and conclusions

Due to the complexity and a large variation of environmental data sets, the application of geostatistical and multivariate statistical methods is recommended. In this study, 56 groundwater samples were used to estimate the spatial variation of some chemical parameters of groundwater in Shiraz plain. The first objective was to investigate and map the groundwater quality using geostatistics. Lack of data in northern and southern parts of the study area was a significant issue, and it was a reason to apply the geostatistical analysis in this investigation. Analysis of the spatial coherence of the variables was performed using the selected models, and the kriging, cokriging and IWD methods were ultimately used to describe the spatial distribution of the parameters. The results obtained through these methods were compared by RMSE and MAE, and it is found that the cokriging model is the most optimal technique for studying the spatial variation in groundwater quality parameters.

EC values 2,696.8 μS/cm, high values of EC in the western parts of the plain could be associated with the lithological formations composed of marls and evaporates. Based on SAR values, it is concluded that the majority of groundwater samples are relatively suitable for irrigation use. The final map showed that EC in central part of the region, where the Sepidrood River meets the Caspian Sea, is dramatically high, which will threaten the sustainability of rice cultivation in the area. The other factors were in suitable level.

High Cl^- values may be attributed to the upcoming or lateral movement of old saline groundwater. The salinity may be attributed to long residence time of water and the dissolution of minerals, followed by evaporation of rainfall and irrigation returns [4]. After short rain events and irrigation periods, the water is consumed by evapotranspiration, and salts are precipitated. During the large rainfall or irrigation, these salts are dissolved and leached into the subsurface [48]. The high sulfate (SO_4^{2-}) concentrations in groundwater could be associated with the dissolution of the mineral pyrite (FeS_2) [49].

Special distribution is governing changes of physical and chemical characteristics of water resources parameters, and even spatial structure of water variables could change in various geographic directions too [42]. This study had attempted to predict the spatial distribution and uncertainty of important groundwater quality indices in the southeast of Iran, Shiraz, using three interpolation techniques (kriging, cokriging and IDW). The analysis showed that for more groundwater quality variables (Mg^{2+}, Ca^{2+}, TH, EC, SO_4^{2-} and Cl^-), cokriging technique performed better

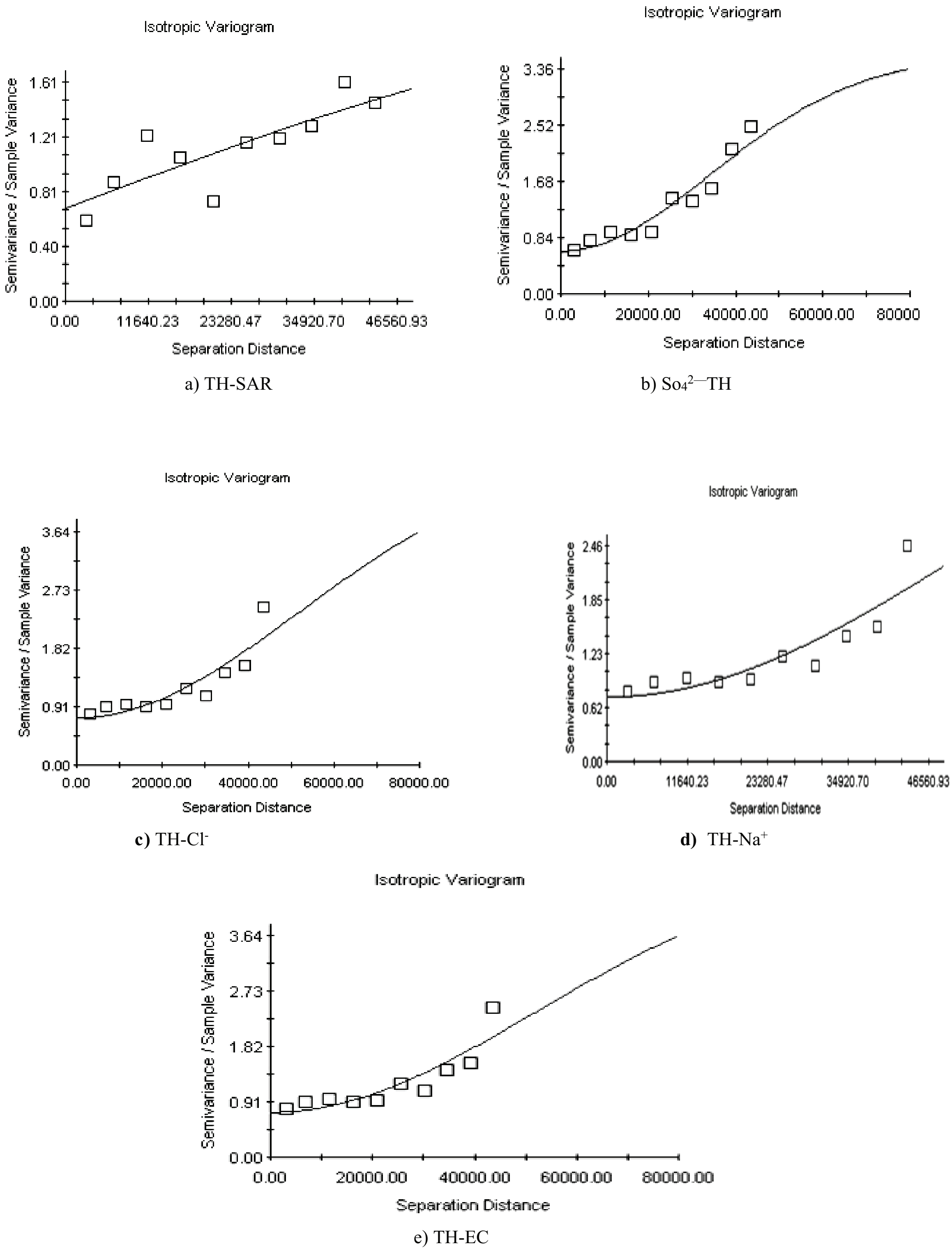
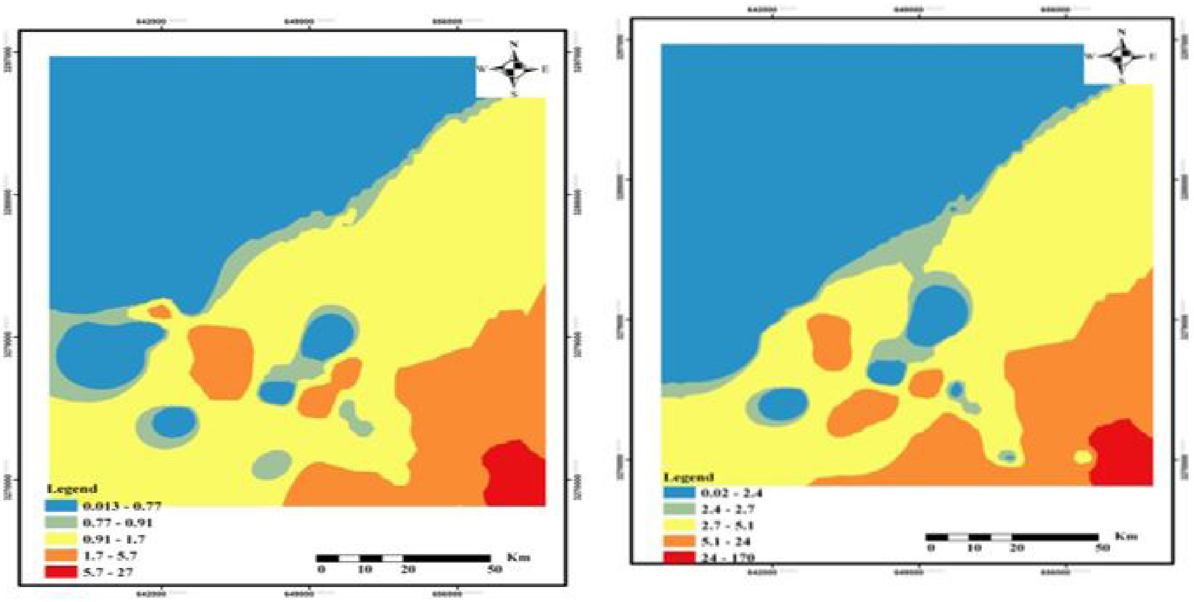


Fig. 5. Cross-variogram of groundwater quality: (a) TH-SAR, (b) SO_4^{2-}–TH, (c) TH-Cl^-, (d) TH-Na^+ and (e) TH-EC.

than kriging and IDW techniques in characterizing the spatial variability. IDW technique is only for some groundwater quality variables like SAR and Na^+ that has better result than kriging to simulate groundwater quality variables. As seen in the variogram results (Table 3), the most appropriate model suited to groundwater quality variables is exponential model. However, the results of the current study show medium spatial structure of the variable data, but the most appropriate results based on the statistical comparisons showed high capability of cokriging technique. Assessment

Table 4
Selecting the best interpolation method according to RMSE and ME parameters

GWQI		Kriging	Cokriging	IDW			
				Exp. 1	Exp. 2	Exp. 3	Exp. 4
pH	RMSE	0.2	0.302	0.204	0.32	0.32	0.236
	MEA	–0.008	0.02	0.003	–0.006	–0.009	–0.008
TH (meq/L)	RMSE	907.5	835.44	928.14	935.07	950.21	973.73
	ME	–20.24	–34.31	–115.302	–105.31	–92.08	–80.35
SAR	RMSE	3.84	3.21	3.75	3.31	2.95	2.78
	MEA	–0.01	0.005	–0.207	–0.016	0.156	0.282
EC (μS/cm)	RMSE	2,724.9	2,695	2,716	2,698	2,743.8	2,831
	MEA	–160.94	–24.151	–269.3	–178.3	–85.69	–15.79
SO_4^{2-} (meq/L)	RMSE	13.423	8.133	12.88	13.368	13.929	14.489
	MEA	–0.34	0.013	–1.117	–1.001	–0.847	–0.714
Cl^- (meq/L)	RMSE	28.97	21.22	32.560	29.32	26.73	25.67
	MEA	–0.642	–21.92	–2.869	–1.395	–0.027	0.97
Na^+ (mg/L)	RMSE	20.75	20.63	24.47	21.831	19.65	18.66
	MEA	–0.067	–21.24	–1.69	–0.482	0.628	1.441
Ca^{2+}	RMSE	4.61	4.58	4.85	5.53	5.86	5.99
	MEA	–0.11	–0.179	0.2	0.4	0.56	0.62
Mg^{2+}	RMSE	2.18	2.54	2.546	2.55	2.815	2.91
	MEA	0.033	0.012	0.231	0.54	0.54	0.66



a) SAR b) Na^+

Fig. 6. Interpolation groundwater quality map based on IDW a) SAR and b) Na^+.

of effective range of various parameters shows that some variables like Cl^- and SO_4^{2-} have narrow effective range. Therefore, for their evaluation grading to be considered with narrow distance. All physical and chemical water quality parameters that have been investigated in this research have high value of ($C_0/C + C_0$) parameter, so it could justify the use of geostatistical techniques.

The geostatistical analysis and the produced maps are useful tools for hydrogeologists and engineers to estimate water quality in areas without sampling sites (e.g., in the northern part of the study area). In addition, they are useful in order to protect the groundwater quality and apply a sustainable development strategy for local water management. The results provide important information, while the spatial

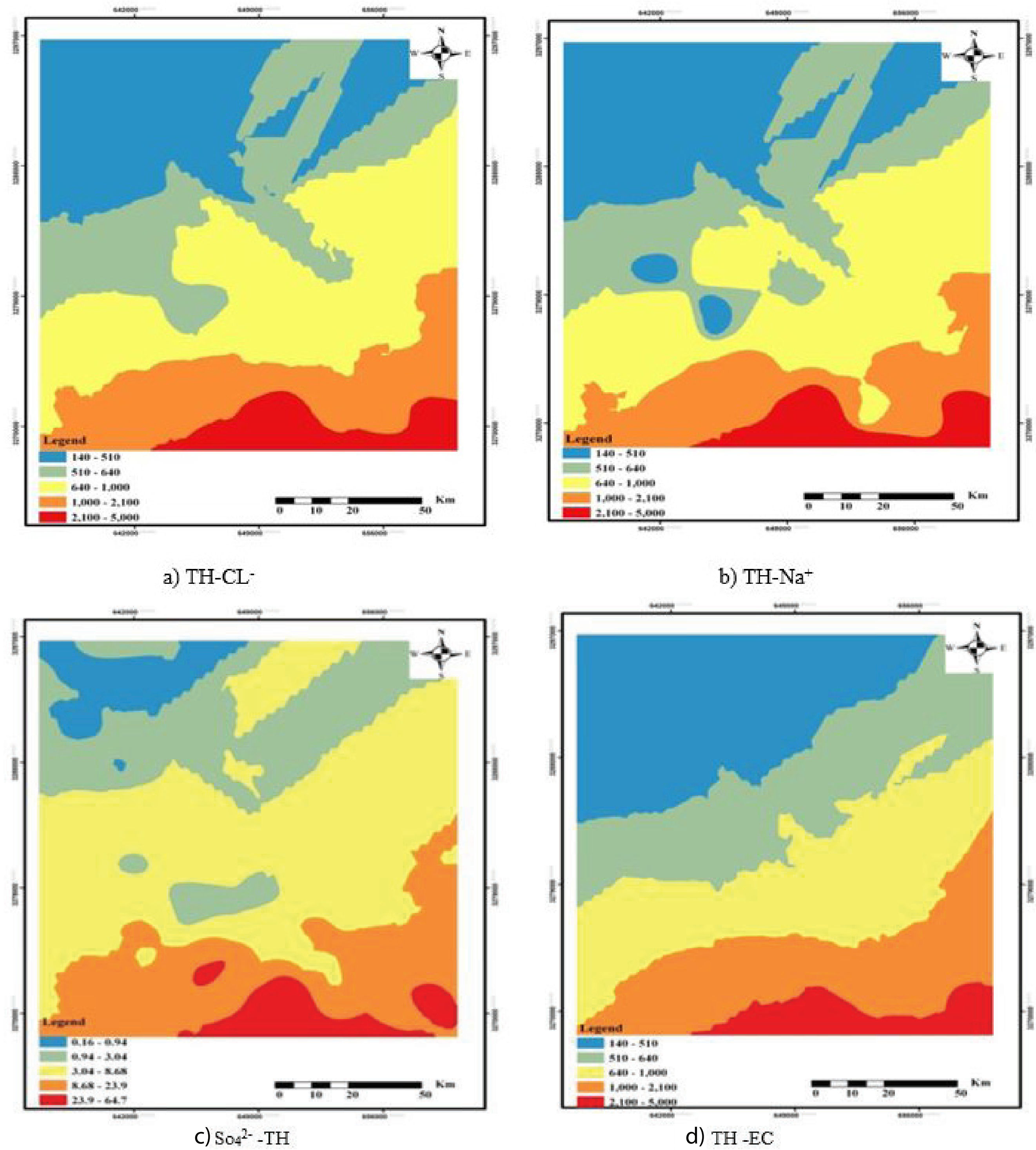


Fig. 7. Interpolation groundwater quality map based on cokriging: (a) TH-Cl$^-$, (b) TH-Na+, (c) SO_4^{2-}-TH and (d) TH-EC.

distribution maps of groundwater quality could potentially be used by local authorities and decision makers in order to assess vulnerable zones and prevent further pollution of already contaminated areas [45]. For example, prior to drilling new boreholes, groundwater quality maps produced from the investigation site should be taken into account by local authorities [44]. This study shows the high capability of geostatistical tools for provision of maps of spatial structure of groundwater quality variables. The results also confirm the research conducted by Rokbani et al. [46] and Zehtabian [47] in which they concluded that geostatistical tools like kriging have high capability for simulating groundwater quality variables. The main perception of the study is that each method depends on the region, sample distribution and other regional characteristics.

Further hydrochemical studies should be carried out to investigate the impacts of land use and anthropogenic activities on groundwater quality in the study area. Factors influencing the groundwater quality should be addressed as early as possible and kept as minimum as possible [36]. Finally, future investigations of the groundwater quality in the study area would benefit by the improvement in hydrogeological and hydrochemical data monitoring. The results of this study can be used to make recommendations for the better management and modeling of soil and plant relationships in future studies.

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